University of Huddersfield Repository

Zhu, Hao, Blunt, Liam and Jiang, Xiang

Flexible shape extraction for micro/nano scale structured surfaces.

Original Citation

FLEXIBLE SHAPE EXTRACTION FOR MICRO/NANO SCALE STRUCTURED SURFACES

H.Zhu, L.Blunt And X.Jiang

Centre for Precision Technologies

Computing and Engineering, University of Huddersfield, Queensgate, Huddersfield HD1 3DH, UK

ABSTRACT

Surface feature is the one of the most important factors affecting the functionality and reliability of micro scale patterned surfaces. For micro scale patterned surface characterisation, it's important to extract the surface feature effectively and accurately. The active contours, known as "snakes", have been successfully used to segment, match and track the objects of interest. The active contours have been applied to facial boundary detection, medical image processing, motion correction, etc. In this paper, surface feature extraction techniques based on active contours have been investigated. Parametric active contour models and geometric active contour models have been presented. Also, a group of examples has been selected here to demonstrate the feasibility and applicability of the surface pattern extraction techniques based on active contours. At last, experimental results will be given and discussed.

Keywords Active contours, snakes, micro-scale features extraction

1   INTRODUCTION

The manufacture and fabrication of Micro-scale devices is now a hugely expanding technology, for instance, Micro-Electro-Mechanical Systems (MEMS). MEMS is the integration of mechanical elements, sensors, actuators, and electronics on a common silicon substrate through microfabrication technology. MEMS are made up of components between 1 to 100 micrometres in size. New applications of MEMS are being developed almost daily, devices such as automotive air bags sensors, pressure sensors, microfluidic devices and micro lens arrays are common. Figure 1 shows some representational applications. For these micro-scale devices, the surfaces were designed to increase efficiency over the traditional macro scale versions better integration and construction at the small size.

It is recognised that surface features are one of the most important factors affecting the functionality and reliability of the micro-scale devices. It is therefore vital that techniques are available which can accurately and reliably characterise these micro scale patterned surfaces. To achieve this, it is essential to extract the geometrical features from the micro-scale surface. There are many methods for feature extraction in the literature. These methods can be classified based on the level of information used. Low-level feature extraction approaches use only image information in segmentation, such as region growing, clustering, and boundary detection using a thresholding or histogram technique. As such, only basic features that can be extracted automatically without any shape information or information about spatial relationships being defined. Some methods incorporate higher-level information in the segmentation process other than only image information, for example, finding shapes by matching. But this implies knowledge of a model, mathematical or template of the target feature [1]. For some micro-scale features, it might be that the exact shape is unknown or that shape is difficult to parameterise, for example the laser etched landing zone of hard disk surface. In this case, a flexible technique based on active contours or "snakes" algorithm can evolve to the target solution.

An active contour is a set of points that aims to enclose a target feature i.e., the feature to be extracted. It is analogous to using a balloon to find a shape. An initial contour is placed outside the target feature, and is then evolved (deflated) so as to enclose it. Then by taking air out of the balloon, making it smaller, the shape is found when the balloon stops shrinking, it then approximates the target shape [2]. By this manner, active contours arrange a set of points so as to describe a target feature, by enclosing it. Active contours are expressed as an energy minimization process. The feature is a minimum of a suitably formulated energy function. This energy functional includes more than just edge information, it includes properties that control the way in which the contour can stretch and curve [3].

2   ALGORITHMS FOR ACTIVE CONTOURS METHOD

An active contour represents a compromise between its own properties, such as its ability to bend and stretch and image properties, such as the edge magnitude. Accordingly, the energy functional is the addition

of a function of the contour's internal energy, its constraint energy and the image energy. The energy functional is termed the snake model, hence E_{snake} is then:

$$E_{snake} = \int_{s=0}^{1} E_{int}\left(v(s)\right) + E_{image}\left(v(s)\right) + E_{con}\left(v(s)\right)ds \qquad (1)$$

The snake model has the advantage of its simplicity and efficiency by its competitive performance. For the implementation of a snake, to evolve a set of points to minimize equation 1, we can use finite elements or finite differences, which is complicated. If a so called "greedy algorithm" methods is used, the energy minimization process become a purely discrete algorithm which is more efficient, illustrated in Fig.2.

The greedy algorithm evolves the snake in an iterative manner by a local neighborhood search around contour points to select new ones which have lower snake energy [4]. At each iteration, all contour pointes are evolved and the process is repeated for the first contour point.

According to the greedy snake, a deformable contour $V(s)$ has a length s as a parameter under regular mapping as follows. $V : \Omega = [0,1] \rightarrow R^2$, $V(s) = [x(s), y(s)]$, where $s \in \Omega$, the energy function has the form:

$$E_{snake}[V(s)] = \int_{\Omega} \left\{ E_{int}[V(s)] + P_{image}[V(s)] \right\} ds \qquad (2)$$

The internal resistance term E_{int} imposes the regularity on the curve by bending and stretching, and can be defined as:

$$E_{int}[V(s)] = \alpha(s)E_{cont}[V(s)] + \beta(s)E_{curv}[V(s)] \qquad (3)$$

Also, the image attraction term P_{mage} serves as a potential field that attracts the snake towards salient image features like lines, edges, regions and textures, and can be defined as:

$$P_{image}[V(s)] = \gamma(s)P_{feature}[V(s)] \qquad (4)$$

The deformable curve is then changed iteratively by minimizing its energy function E_{snake}. The final position corresponds to the minima E^*_{snake} of E_{snake}:

$$E^*_{snake} = \min\left\{ E_{snake}[V(s)] \right\} = \min\int_{\Omega} \left\{ E_{int}[V(s)] + P_{image}[V(s)] \right\} ds \qquad (5)$$

In this research, we will use the greedy algorithm and its variation as a first attempt of achieving a segmentation in a highly intuitive and efficient way.

Another method to implement the snake model is to use the concept of Geometric active contour. (GAC) models have been introduced, where the curve is represented implicitly in a level set function. Level set methods were first introduced by Osher and Sethian [5].

The basic idea is to represent contours as the zero level set of an implicit function defined in a higher dimension, usually referred to as the level set function, and to evolve the level set function according to a partial differential equation. This approach presents several advantages over the traditional parametric active contours. First of all, the contours represented by the level set function may break or merge naturally during the evolution, and the topological changes are thus automatically handled. Second, the level set function always remains a function on a fixed grid, which allows efficient numerical schemes. In level set formulation of active contours, denoted by C, contours are represented by the zero level set $C(t) = \left\{ (x, y) | \Phi(t, x, y) = 0 \right\}$ of a level set function $\Phi(t, x, y)$. The evolution equation of the level set function Φ can be written in the following general form:

$$\frac{\partial \Phi}{\partial t} + F|\nabla \Phi| = 0 \qquad (6)$$

The function F is called the speed function. For image segmentation, the function F depends on the image data and the level set function Φ.

In traditional level set methods, the level set function Φ can develop very sharp shape during the evolution, which makes further computation highly inaccurate. To avoid these problems, a common numerical scheme is to initialize the function Φ as a signed distance function before the evolution, and then re-initialize the function Φ to be a signed distance function periodically during the evolution. Indeed, the re-initialization process is crucial and cannot be avoided in using traditional level set methods.

Re-initialization has been extensively used as a numerical remedy in traditional level set methods. The standard re-initialization method is to solve the following re-initialization equation:

$$\frac{\partial \Phi}{\partial t} = sign(\Phi 0)(1 - |\nabla \Phi|) \tag{7}$$

In implementing the proposed level set method, the time step can be chosen significantly larger than the time step in traditional level set methods. Using a larger time step can speed up the evolution, but may cause error in the boundary location. So, the balance lies between the speed of the evolution and accuracy in boundary location.

3   EXPERIMENTAL RESULTS

The proposed active contours based feature extraction methods have been applied to a variety of micro scale patterned surfaces. All the experimental results are shown in this section, otherwise, the comparison between different algorithms is presented. Fig. 3 shows the laser etched landing zone of hard disk surface, measured using a white light interferometer, Talysurf CCI. Fig.4 shows the experiment results based on greedy algorithm snakes of the micro-chip pin surface. Also, the comparison is shown in Fig. 5. From the results it is clear the snakes based on greedy algorithm cannot handle concave contour. The GAC have a better performance in extraction the concave feature.

4   CONCLUSIONS

In this paper, the basic principle and framework of active contours are introduced. To extract the Micro-scale Surface Feature flexibly and accurately, the active contours methods are implied. Respectively, greedy snakes and geometric active contour models have been presented. The feature extraction technique based on greedy algorithm and level set method has been investigated. The measured data and the experimental results based on different algorithms are given and compared.

REFERENCES

[1]   M. Kass., A. Witkin, and D. Terzopoulos, Snakes: Active contour models, Int. J. Comput Vision, 1(4), pp. 321-331, 1988.

[2]   D. Cremers, M. Rousson and R. Deriche, A review of statistical approaches to level set segmentation: Integrating color, texture, motion and shape, Int. J. Comput. Vision, 72(2), pp. 295-313, 2007.

[3]   L.D. Cohen and I. Cohen, Finite-element methods for active contour models and balloons for 2-D and 3-D images, IEEE Trans. Pattern Anal. Mach. Intell. 15 (11), pp.1131–1147. 1993.

[4]   R. Ronfard, Region-based strategies for active contour models, Internat J. Comput. Vision 13 (2), pp.229–251. 1994.

[5]   S. Osher, J. A. Sethian, Fronts propagating with curvaturedependent speed: algorithms based on Hamilton-Jacobi formulations, J. Comp. Phys., vol. 79, pp.12-49, 1988.
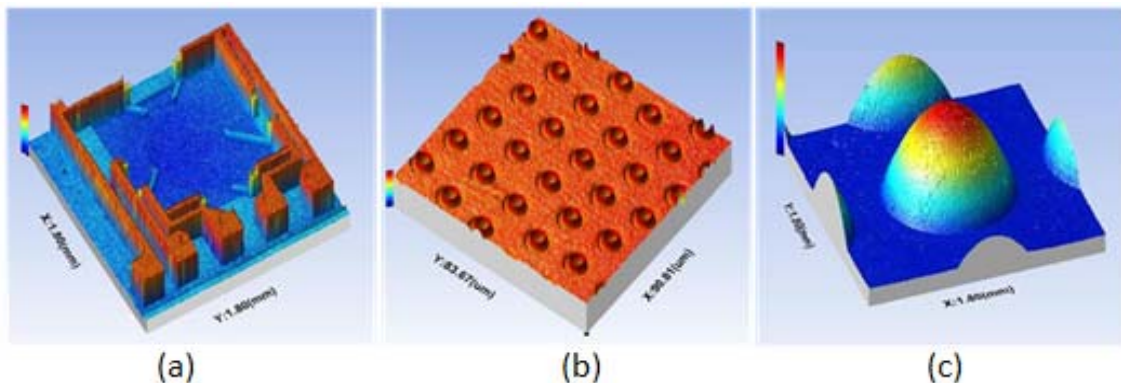
Figure 1: MEMS-based acceleration sensor (a), laser etched landing zone of hard disk surface (b) and micro optical arrays (c)
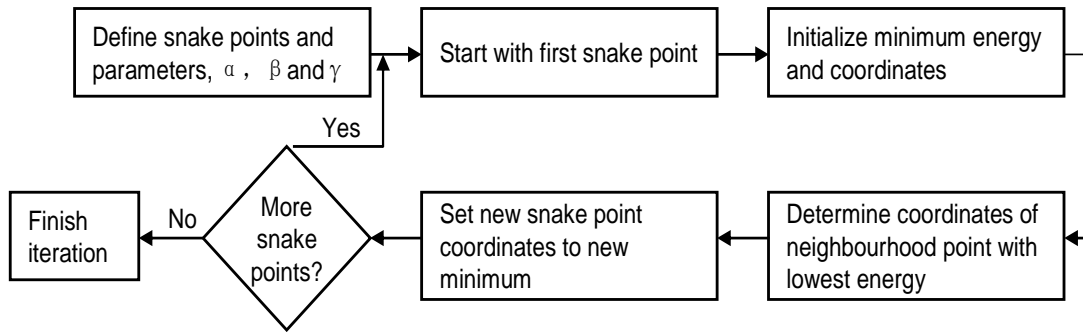
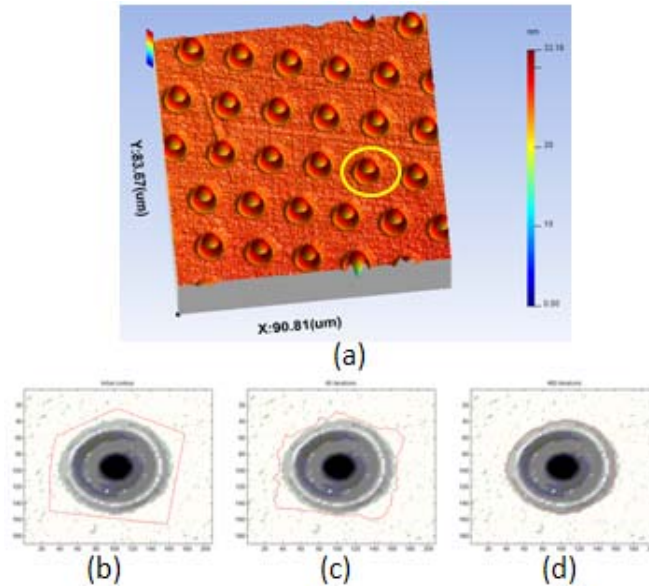**Figure 2: Operation of the greedy algorithm**

Figure 3: laser etched landing zone of hard disk surface (a) and the analysis results based on GAC, respectively after 20, 200 and 360 iterations (b-d)
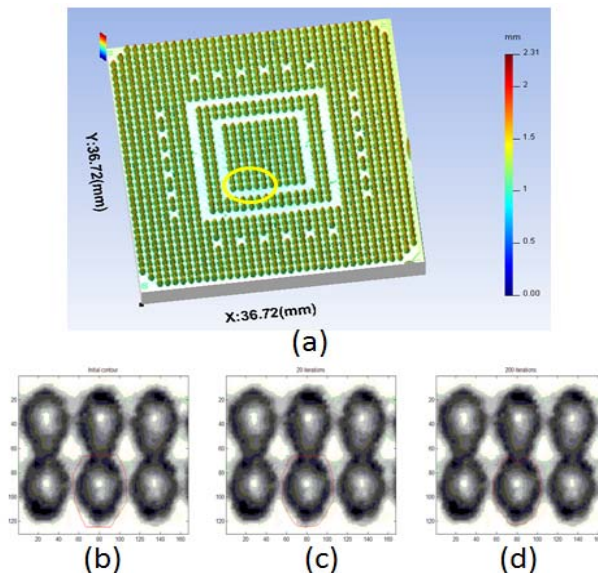

Figure 4: (a) micro-chip pin surface features extracted by active contour based on greedy algorithm (b-d)
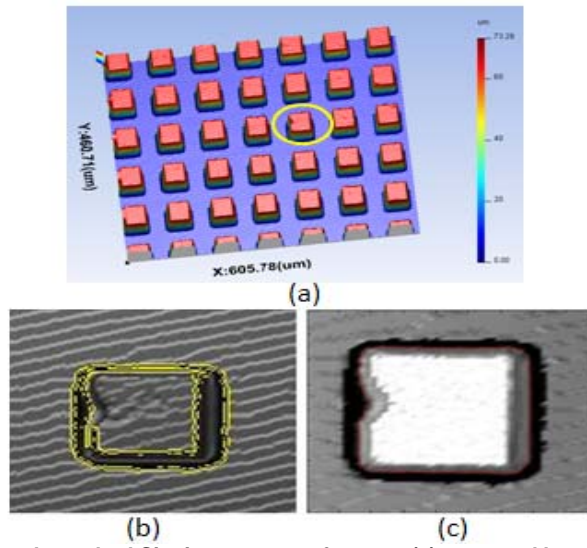
Figure 5: comparison between the etched Si microstructure features (a) extracted by active contour based on greedy algorithm (b) and GAC (c)